Online Healthcare Platform Evolution: The Interplay of Bargaining and Network Effects

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Abstract

Online healthcare platforms are rapidly emerging worldwide as a healthcare business model. This is because they have the potential to scale very fast, providing healthcare access to a large number of consumers. This scaling depends on the speed of adoption (of the platform) by both healthcare providers and consumers, which the platforms can influence via economic incentives. For example, most platforms charge healthcare providers a fee to get access to consumers, and this fee is usually arrived at via a bargaining process. As is common in bargaining settings, agents with higher relative bargaining power are able to extract better terms. In platform settings, agents who have a stronger ability to induce agents on the other side of the platform to adopt have more power. In this paper, we build a novel framework that integrates theories from the network effects and bargaining literatures. We test our theoretical predictions using data from a Chinese online healthcare platform. Our empirical approach is able to precisely quantify the relationship between network effects, bargaining power and final prices in this market. Using a series of simulations, we show how these results can help the platform balance the conflicting objectives of growth and profitability.

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Keywords

Healthcare, Online Platforms, Bargaining, Network Effects

Introduction

Healthcare expenditure accounts for between 5% and 20% of all national expenditure for most countries.[1] With the population of most countries aging, this proportion is likely to get higher in the coming years. At the same time, accessibility and equity of healthcare are critical challenges for a significant part of the world's population.[2] Advances in digital technologies hold significant promise in terms of addressing accessibility and equity issues, especially in large markets, both in terms of population size and geography.

One specific digital healthcare model - online platforms - holds considerable promise in terms of improving healthcare access and use.[3] While there are many reasons for this, the most important one is that online platforms can scale quickly due to the "flywheel" effect - formally, the cross-network effect - as more sellers (healthcare providers) that join induce more buyers (patients) to join, who in turn induce additional sellers to join and so on.[4] The key to growth for a new online platform is this flywheel effect and hence managers of such platforms focus on providing incentives to both sellers and buyers to join the platform as quickly as possible. The most common incentive is an economic one operationalized via prices (to join and/or continue transactions on the platform). Given that the sellers on these online platforms in the healthcare industry are medical institutions (hospitals, clinics, healthcare systems etc.), it turns out that the final prices charged to them are arrived at via a bargaining process. Table 1 lists multiple examples of online healthcare platforms all over the world that use bargaining in the price setting process.[5]

[1] https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS.

[2] https://www.who.int/news/item/13-12-2017-world-bank-and-who-half-the-world-lacks-access-to-essential-health-services-100-million-still-pushed-into-extreme-poverty-because-of-health-expenses.

[3] https://www.forbes.com/sites/sethjoseph/2021/05/17/healthcare-delivery-disrupted-the-rise-of-platforms-in-healthcare/.

[4] https://www.forbes.com/sites/forbescoachescouncil/2018/01/02/how-to-harness-the-power-of-network-effects/?sh=204e6b2862e8.

[5] Note that bargaining is also prevalent in offline healthcare markets, as is typical in any business-to-business price setting process. Previous studies have yet to explicitly quantify the cross-network effects and measure its impact on the bargaining outcomes.

Table 1. Online Healthcare Platforms That Use Bargaining as Part of Pricing

Online Healthcare Platform	Services	Businesses Served	Consumers Served	Country
AhoraDoctor	Primary Care	Health organizations	Patients	Argentina
Aledade	Primary Care	Community health centre, large practices, solo physicians	Patients	United States
AssistMe	Elderly Care	Nursing homes	Seniors	Germany
DadaDoc	Telemedicine	Doctors	Patients	Morocco
Focal Company	Physical Health Exam	Private hospitals, public hospitals, special clinics	Patients	China
Haodf	Telemedicine	Hospitals, doctors	Patients	China
HealthForce	Telemedicine	Clinics	Patients	South Africa
KareXpert	Electronic Health Record Integration	Healthcare provider organizations	Healthcare providers	India
Memed	E-prescriptions	Hospitals, doctors	Patients	Brazil
Quartet Health	Mental Health Care	Referring providers, mental health providers	Patients	United States
uPaged	Nurses	Healthcare Organizations	Nurses	Australia
Vericred	Data Connectivity Infrastructure	Health Insurance and employee benefit carriers	Insurance clients	United States
Vidmed	Telemedicine	Hospitals, doctors	Patients	India

In order to build a viable business serving the entire ecosystem, the online platform needs to manage the tension between market expansion or growth and profitability. The former comes via the flywheel, while the latter comes via price-setting via bargaining. In other words, the platform needs to manage the relationship between the cross-network effect and its bargaining strategy. However, there is virtually no extant literature that investigates this relationship. In this paper, we draw on theory and methods from two disparate literatures - network effects and bargaining - to develop a conceptual framework that allows us to delve into this relationship. We do this by leveraging the institutional setting and data from a large and leading online healthcare platform in China from its inception.[6] Specifically, based on extant theory, we develop hypotheses pertaining to network effects (both direct and cross) and their moderators, bargaining (including the role of multiple attributes and heterogeneity) and, most importantly, the link between the two.

Our results show that online healthcare platforms can indeed be seen as an important business model in healthcare ecosystems. This is based on our finding that both direct and cross-network effects are positive, accelerating healthcare accessibility for consumers. On the bargaining side, we find that, as expected, the bargaining power of both hospitals and the platform plays a big role in determining outcomes. For example, all else being equal, more prestigious

[6]Given its size, China is currently the world's second largest "MedTech" market, accounting for 19% of worldwide medical technology expenditure. See https://www.ice.it/it/sites/default/files/inline-files/Summary%20Market%20Research%20Medtech%202019_0.pdf for details.

hospitals are able to extract better contract terms from the platform. Similarly, in markets where the platform has a higher consumer penetration, all else being equal, it can extract better contract terms from the hospitals in those markets. The most interesting and novel finding pertains to the role of the cross-network effect. Hospitals that have a higher cross-network effect i.e., induce more consumers to join the platform, extract much better terms from the platform. To the best of our knowledge, this is the first documentation of the impact of the cross-network effect on bargaining outcomes in online markets.

These results have important ramifications for online healthcare platforms in terms of their strategy and resource allocation. Our framework allows platforms to choose which types of hospitals to target at different points in the evolution of the platform based on their objective. For example, if a platform places a higher weight on revenue and profits as opposed to growth, it should allocate its resources towards hospitals with smaller cross-network effects. On the other hand, a platform could give up short-term profits to bring hospitals with high cross-network effects on board to enable faster growth. We illustrate this in detail via a series of policy simulations using the results from our analysis and a variety of initial conditions. We also translate these findings into (conservative) cost savings for consumers.

Overall, our paper makes the following four contributions. First, it sheds light on a new business model - online platforms - that has the potential to dramatically improve accessibility to healthcare, especially in markets that are underserved. Second, it proposes a conceptual framework that integrates theories from two disparate literatures to describe the potential evolution of online healthcare platforms. Third, it quantifies how an agent's network power, measured via the cross-network effect, translates into better economic outcomes vis-a-vis pricing in bargaining settings. Finally, it provides strategic resource allocation guidelines for online healthcare platforms as they deal with the conflicting objects of growth and profitability. In fact, our approach can be adapted to online platforms in any industry vertical in any geographic market.

Institutional Setting, Theory and Hypotheses

In this section, we first detail the relevant features of our setting. We then use existing theory to develop hypotheses that we test with the available data.

Institutional Setting

Our setting is the market for physical health exams in China. This is a very large market with 4.64 billion exams being conducted in 2020 at a value of 176.7 billion Yuan (about 28 billion USD).[7] Despite the large absolute numbers, the coverage is still relatively low at 35%.[8] With the steady growth of the healthcare expenditure and the public awareness of preventive medical care in China, the market is expected to continue expanding rapidly in the coming years.

Selling physical health exams online is a relatively recent phenomenon in the Chinese healthcare market. The focal company, established in 2015, is a leading physical health exam online platform in China. The platform consists of a hospital side and a consumer side. Hospitals list physical health exam packages on the platform. These physical health exams generally are preventive in nature, typically performed on asymptomatic patients for periodic screening. These are initiated by consumers and their cost is not covered by insurance companies. There is a wide range of physical health exam packages, designed for different age groups (teenager, middle-aged, elderly, etc.), for different concerns (cardiovascular, diabetes, women's health, etc.), for different purposes (driver's license application, job application, marriage certificate application, etc.), and performed by different hospitals (public hospitals, private hospitals, and special clinics).

Compared to the traditional physical health exams, the online physical health exam platform provides benefits for consumers and hospitals. The traditional process for Chinese consumers to get a physical health exam is as follows: (1) visit the hospital and register for the exam, (2) wait (often in long queues) in the hospital to have the exam done, (3) wait for the exam results, (4) go back to the hospitals to pick up the exam results or wait for the exam results to be mailed, (5) make an appointment with a doctor for consultation in case of abnormal results,

[7]Sources: https://www.statista.com/statistics/976557/china-medical-check-up-market-size/ and https://m.huaon.com/detail/726620.html.

[8]Source: http://www.leadingir.com/trend/view/3767.html.

and (6) wait for the doctor to discuss the results. The use of the online physical platform has at least four benefits for consumers: (1) making the appointment online saves them time and hassle, (2) exam results are accessed via the platform's mobile app, obviating a follow-up trip to the hospital, (3) they have access to the platform's large database, FAQs and discussion forums for free interpretation of exam results, and (4) in case of abnormal results, they can consult a doctor on the online platform for 10 minutes free of charge and for a nominal fee beyond that, saving money on a doctor consultation in the physical world. For hospitals, the benefits are access to expanded pool of consumers, easier scheduling and operations, differentiation from competitors and the ability to signal use of the latest technology.

As noted earlier, the key for the platform is to get adoption by both consumers and hospitals. The platform tries to lower the adoption barrier by not imposing any explicit joining fee or cost for either side. On the consumer side, all consumers need to do is to register on the platform before making a purchase. The registration is free but requires consumers to provide their names and cellphone numbers for verification purpose. The cellphone number contains location information at the city level.[9] Hospitals also do not need to pay any fee to the platform to be listed. The hospitals, however, incur indirect costs, such as administrative costs of preparing hospital information to be uploaded, creating physical health exam packages to be uploaded and integrating the hospital information system with the platform's system.

With respect to adoption, the platform focuses most of its effort on hospitals, relying on informal mechanisms such as word-of-mouth for consumers. On the hospital side, the platform employs sales teams to communicate with hospital administrators about the benefits of joining the platform. The sales teams work locally and are given geographic exclusivity. If a hospital agrees to join the platform, the relationship is formalized via a signed contract, the terms of which are arrived via a bargaining process. The two terms that a contract is defined over are the "discount" level and the clearing cycle (details on both these below). The nominal duration of a contract is a year (with automatic renewal). However, contract terms can be and often are renegotiated before the renewal deadline.

The discount level is defined as the difference between what the platform collects from the

[9] In China, a cellphone number can usually predict a user's location based on a combination of location services and a household registry.

consumer and what it pays to the hospital. In other healthcare contexts, it is referred to as the "contractual allowance" (Dranove et al., 1993; Sorensen, 2003). The platform collects the *list price* for each exam package from the consumer and pays the hospital $(1-discount)\times list\ price$. The total profit for the platform is $(listprice \times discount \times units\ \ sold)$. As a result, the platform always prefers a larger discount while hospitals prefer a smaller one. The discount level is probably the most important contract term as it directly impacts the platform's profit.

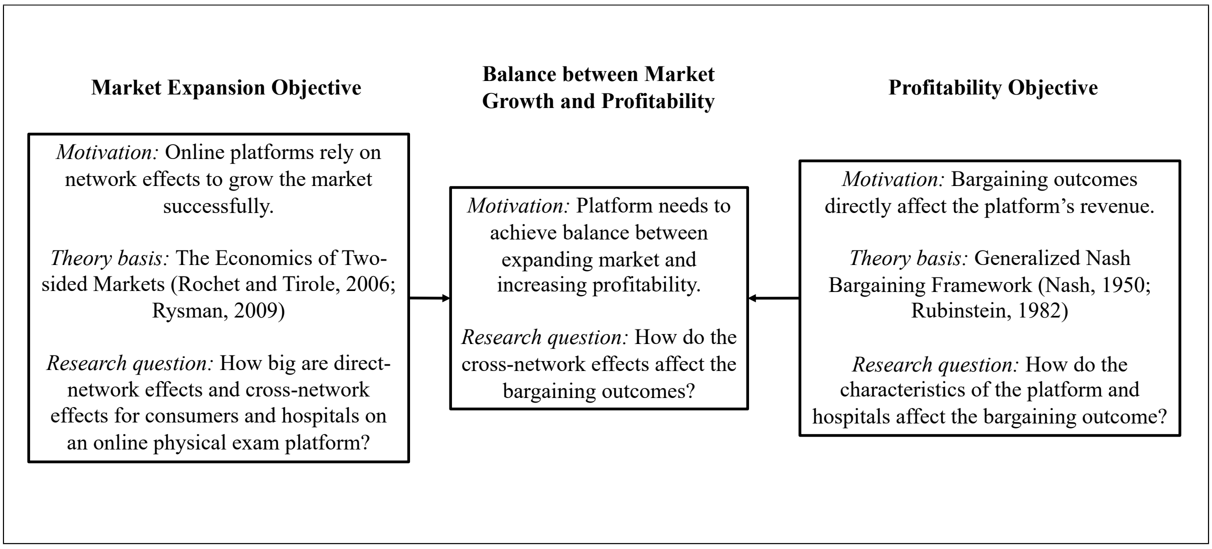
The second contract term is clearing cycle which is defined as the frequency at which the platform makes payments to hospitals. The clearing cycle can be set at daily, weekly, monthly, or quarterly i.e., the platform reimburses hospitals each day, week, month or quarter. A longer clearing cycle means that the platform gets to hold the reimbursement (revenue) for a longer period, improving its liquidity and working capital. Liquidity is a key factor in determining a startup's survival and success (Brown et al., 2009; Holtz-Eakin et al., 1994; Oliveira and Fortunato, 2006), and thus the platform prefers as long a clearing cycle as possible. Liquidity tends to be a less serious concern for hospitals (as their cash flows are more stable and predictable). As a result, relative to the platform, hospitals are less focused on the clearing cycle during the bargaining process.

Theory and Hypotheses

We now turn to theory to help in developing the conceptual framework and the formulation of specific hypotheses. As noted earlier, the platform has two conflicting objectives in its initial stage of business: market expansion and profitability. At a high level, the theory of network effects underpins the market expansion objective while the theory of bargaining (and price setting) underpins the profitability objective. Given that there is no research available that explicitly quantifies the tradeoff between these two objectives in platform settings, we develop a framework that connect the theoretical work in these two domains. A pictorial depiction of our conceptualization can be seen in Figure 1. As can be seen from the figure, a key contribution of our research is its ability to help the platform achieve the balance between its two conflicting objectives.

Using the figure as a guide, we delve into the theories underpinning market expansion

Figure 1. Theoretical Underpinnings and Research Questions



(network effects) and profitability (bargaining) and their interconnection next.

Theory and Hypotheses: Direct-Network Effects

In two-sided markets, direct-network effects arise when a given user's adoption or usage is influenced by other users of the same product or service (Birke, 2009). The direct-network effect can be positive or negative depending on a series of market conditions.

Previous studies have documented that the following factors contribute to a positive direct-network effect: positive word-of-mouth (e.g., Godes et al., 2005; Libai et al., 2013), observational learning (e.g., Chen et al., 2011; Joshi and Musalem, 2021), pressure from earlier adopters (e.g., Bass, 1969; Mahajan et al., 1995), and a value increase caused by an increasing number of adopters (e.g., Goolsbee and Klenow, 2002). In contrast, there exist factors that contribute to a negative direct-network effect: crowding out or congestion effect (e.g., Vitorino, 2012), and matching issues (e.g., Akbarpour et al., 2021; Fong, 2020).

In our setting, congestion would play a role on the consumer side if a consumer could not get access to physical health exams at a given hospital because other platform consumers have taken up all possible slots. However, congestion on the online platform is unlikely to happen because online sales only account for a tiny fraction of the total capacity at the hospitals. In addition, unlike ride-sharing or dating platforms, the physical health exam market is not based one-to-one matching as a consumer could get the same exam at many different hospitals.

Furthermore, it is very likely that the advantages of using the online platform (as noted above) will result in positive word-of-mouth. As a result, on the consumer side, we expect to see positive direct-network effects.

On the hospital side, the joining hospitals were not in close geographic proximity, leading to little direct competition for physical health exams. In other words, there will be no congestion i.e., no negative direct-network effect. In fact, as hospitals observe other hospitals joining the platform, they may feel compelled to join as well in order to not fall behind in terms of product offerings. As a result, we expect the direct-network effect to be positive on the hospital side.

Hypothesis 1a *The direct-network effect is positive on the consumer side on the online physical health exam platform.*

Hypothesis 1b *The direct-network effect is positive on the hospital side on the online physical health exam platform.*

Theory and Hypotheses: Cross-Network Effects

Cross-network effects arise in two-sided markets when the value of the product or service of one side is influenced by the other side's adoption decision (Economides and Himmelberg, 1995; Stobierski, 2020). Similar to direct-network effects, cross-network effects can be either positive or negative across markets.

Previous studies have documented strong positive cross-network effects in many markets - yellow pages (Rysman, 2004), personal digital assistants (Nair et al., 2004), hardware and software (Clements and Ohashi, 2005; Dubé et al., 2010; Stremersch et al., 2007), banking (Ackerberg and Gowrisankaran, 2006), and e-commerce (Chu and Manchanda, 2016; Zhou et al., 2021). On the other hand, negative cross-network effects have been documented in other markets e.g., advertising and TV viewing (Wilbur, 2008).

In our setting, the more the hospitals on the platform, the more the choices for consumers across hospital type and exams (products), distance, prices and convenience. As consumers value product/service variety (Briesch et al., 2009; Clements and Ohashi, 2005; Sun et al., 2016), shorter distance (Chu et al., 2021) and lower prices, we expect the cross-network effect from hospitals to consumers to be positive. For hospitals, the more the consumers on the platform, the higher the potential for revenues. Thus we expect that cross-network effect from consumers to hospitals to also be positive.

Hypothesis 2a *The cross-network effect from hospitals to consumers is positive on the online physical health exam platform.*

Hypothesis 2b *The cross-network effect from consumers to hospitals is positive on the online physical health exam platform.*

Theory and Hypotheses: Heterogeneous Cross-Network Effects

Most of the previous research on network effects only focuses on the impact of size of each side on the network, e.g., the number of hospitals or the number of consumers in our context.

However, in addition to network size, other factors, such as network structure and the characteristics of network participants may also have a significant impact on network effects (Afuah, 2013; Shankar and Bayus, 2003). In business markets, a critical characteristic is the size of the business. For example, Dick (2007), Berry and Waldfogel (2010), and Kugler and Verhoogen (2012) have shown in various industries that business size is positively linked to the average quality of products. Mas-Ruiz and Ruiz-Moreno (2011) have argued that larger firms are perceived with better reputations and higher levels of prestige, which are attractive to consumers. In addition, Pashigian and Gould (1998) and Gould et al. (2005) have shown that larger stores can attract more traffic compared with smaller ones in a shopping mall.

In our setting, hospitals vary in size (number of beds, number of physicians etc.) considerably. This will affect consumer perception of the quality of the hospital side of the platform, affecting their adoption decision. Thus, we have the following hypothesis.

Hypothesis 3 *A hospital's size moderates its cross-network effect on the platform, such that a larger hospital's platform adoption is able to attract more consumers to join the platform.*

Theory and Hypotheses: Interplay between Cross-Network Effects and Bargaining

As noted earlier, platforms need to set prices to induce adoption on both sides. However, an extra factor - the cross-network effect - needs to be considered in pricing in platform settings, in addition to the standard factors such as demand and costs ((Jullien et al., 2021; Rysman, 2009; Sriram et al., 2015)). Further, these prices fall into two types - posted prices (where the platform set the price directly) and negotiated prices (where the prices are determined at the end of a bargaining process).

Extant research in posted price settings has shown that cross-network effects do have an impact on final prices. Ohashi (2003) has shown that aggressive promotions on the consumer side could help a firm to secure the market dominance early on in the VCR market. Clements and Ohashi (2005) have shown that introductory pricing is an effective practice at the beginning of the product cycle due to strong cross-network effects from the consumer base in the video game market. Liu (2010) has shown that hardware firms are willing to cut prices early in order to build up the network and attract more game developers to supply games in video game console markets.

But little empirical work exists in negotiated price settings, which represent a more general case of pricing as posted prices can be seen as case of zero bargaining Rochet and Tirole (2003, 2006). Given that negotiated prices are determined by two parties, rather than being dictated by one party, pricing outcomes are likely to be different between the bargaining case and the posted price case (Adachi and Tremblay, 2020; Zhang et al., 2021). In order to develop our hypothesis, we rely on the theoretical result in this literature that the side with a stronger positive cross-network effects would receive lower prices so that the platform can grow quickly (Armstrong, 2006; Caillaud and Jullien, 2003; Rochet and Tirole, 2003, 2006). Specifically, in our setting, all else being equal, the platform would be willing to settle for lower prices in the negotiation process for hospitals that have higher cross-network effects. This leads us to the following hypothesis.

Hypothesis 4 *A hospital's cross-network effect is positively correlated with its bargaining outcome, i.e., negatively correlated with the platform's bargaining outcome, such that the platform receives less favourable contract terms from a hospital with a bigger cross-network effect.*

This is a key hypothesis from both the theoretical and managerial perspectives. Theoretically, it represents, for the first time, a link between the two previously unconnected literatures of network effects and pricing under bargaining.[10] Managerially, if true, it provides a quantitative measure to calibrate the tradeoff between market expansion and profitability with implications on resource allocation and growth planning.

Theory and Hypotheses: Bargaining Power

A key determinant of bargaining outcomes is bargaining power under the generalized Nash bargaining framework (Nash, 1950). Bargaining power determines how the total surplus is split between the two parties. If the total surplus $\$100$ is split as $\$60$ and $\$40$, then the relative bargaining power is 0.6 and 0.4 for the two parties respectively. Next, we will discuss the key characteristics (in our setting) of the two parties in our setting that influence the bargaining power.

One of the most important assets of the platform is its market share on the consumer side. Market share is a key measure of business performance, widely used by firms and investors (Bendle and Bagga, 2016; Katsikeas et al., 2016). Extensive empirical evidence has shown that market share is positively linked to a firm's profitability (Edeling and Himme, 2018). In posted price settings, Boulding and Staelin (1990) and Bhattacharya et al. (2021) suggest that part of the positive relationship between market share and profitability comes from the increased ability to set prices. In our setting, we believe that a higher market share represents higher bargaining power for the platform (due to its ability to deliver a larger number of consumers to hospitals). This increased bargaining power is likely to translate into lower negotiated prices from the hospitals (recall that the lower the price the platform pays to the hospital, the higher its revenue as it keeps more of the retail price).

On other hand, for hospitals, one of their most important assets is their reputation. This reputation is closely tied to the type of hospital - public or private - in China. Public hospi-

[10]A few previous studies have shown *implicitly* that the cross-network effects could impact bargaining outcomes. For example, Ho (2009) and Gowrisankaran et al. (2015) have shown that hospital mergers and acquisitions can lead to higher negotiated prices with health insurers. However, these studies assume stable networks with no entry or growth. They also do not explicitly show and/or model the relationship between the cross-network effects and bargaining outcomes.

tals had long enjoyed a stronger reputation in China, with over 80% market share (Xu et al., 2019)) before 2009, when the Chinese government initiated a National Healthcare Reform. This healthcare reform encouraged the development of private hospitals and competition among various hospitals (Jiang and Pan, 2020). Since then, private hospitals have experienced much faster growth compared to that of public hospitals, accounting for two-thirds of the 33 thousand hospitals in China by 2018.[11]

However, despite the rapid development and growth of private hospitals, their reputation is still not as high as that of public hospitals. This is because of two reasons. First, private hospitals are viewed (on average) as being more motivated by economic incentives e.g., making profits, rather than patient welfare. Second, private hospitals face difficulties in recruiting high-quality medical personnel as they are perceived to be less attractive in terms of job security and employee development opportunities (Deng et al., 2018).

Based on the above, we propose two hypotheses reflecting the impact of bargaining power on negotiated outcomes as follows:

Hypothesis 5 *The platform's bargaining power is positively influenced by the platform's consumer market share.*

Hypothesis 6 *The average bargaining power of public hospitals is bigger than that of private hospitals in China, i.e., the relative bargaining power of the platform is bigger with private hospitals compared to that with public hospitals.*

Theory and Hypotheses: Multi-attribute Bargaining

In many business-to-business (B2B) settings, parties negotiate on multiple attributes of a contract. Such situations are complex and challenging as different parties may have different preferences over different attributes (Lai et al., 2004; Lai and Sycara, 2009). Due to the theoretical complexity of characterising multiple attribute bargaining contracts and also challenges in collecting multi-attribute bargaining data, empirical studies on multiple attribute bargaining are extremely limited.

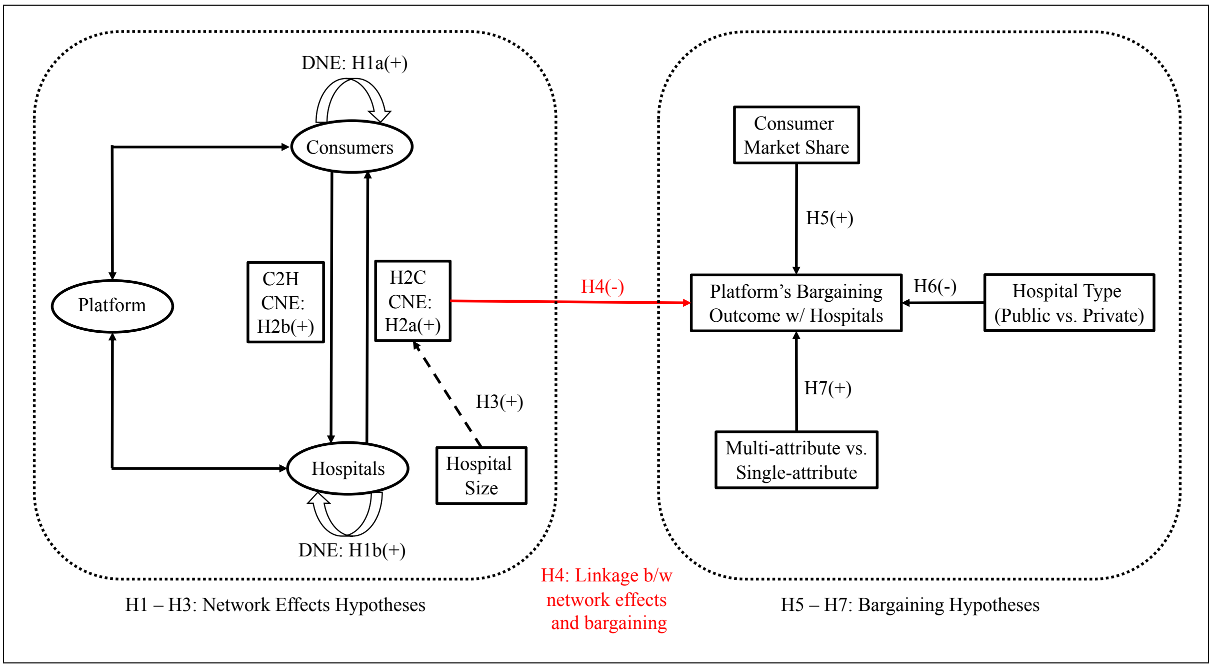
[11] Source: https://www.statista.com/statistics/624593/china-hospital-number-by-ownership

Recall that in our setting, there are two key attributes of a contract that the platform and hospitals bargain on - the discount level and the clearing cycle. Both parties value the discount level, but hospitals generally do not care about the clearing cycle. Compared to bargaining over a single attribute (the discount level), multi-attribute bargaining (over both discount level and clearing cycle) creates additional value that can be shared between the two parties. Given that the platform has a stronger preference towards a longer clearing cycle, we hypothesize that

Hypothesis 7 *The online physical health exam platform is able to capture a bigger share of the total value in the multiple attribute bargaining setting as opposed to the single attribute bargaining setting.*

We conclude this section with Figure 2 that depicts the proposed hypotheses within our conceptual framework. As can be seen from the figure, the left panel pertains to hypotheses underpinning market expansion, while the right panel pertains to those underpinning profitability. The key hypothesis is H4 which links the firm's two conflicting objectives.

Figure 2. Conceptual Framework and Hypotheses



Note: DNE stands for direct-network effects, CNE stands for cross-network effects, C2H stands for consumer-to-hospital and H2C stands for hospital-to-consumer. The dashed line indicates moderating effect.

Model

We need to specify an econometric model in order to test our hypotheses. This model must be able to pin down direct and cross-network effects as well as the bargaining process between the platform and hospitals. The model comprises three parts. The first part models the consumer adoption (of the platform) via a utility-based approach. The second part models the hospital adoption (of the platform) also via a utility based approach. These two parts allow us to obtain the direct and cross-network effects. The third part casts the bargaining process between the platform and the hospital under the Nash bargaining framework. We describe each part in turn below.

Consumer Adoption Decision

We model the indirect utility of joining the online healthcare platform for consumer i in city k province s at time t as

$$U^C_{ikst} = F_C(b^C)H_C(N^C_{s,t-\kappa})G_C(N^H_{k,t-\tau}, Y^C_{st}, W_{kt}, X_{kt}, \eta_k, \xi^C_{kt}, \epsilon^C_{ikst}) - p^C_{ikst} \tag{1}$$

where b^C is consumers' average intrinsic preference towards the platform. To capture the direct-network effect, $N^C_{s,t-\kappa}$ measures the number of consumers that have joined the platform by time $t-\kappa$ in province s.[12] To capture the cross-network effect, $N^H_{k,t-\tau}$ represents the number of hospitals that have joined the platform by time $t-\tau$ in city k. As consumers need to travel to hospitals for the physical health exams, the cross-network effect will arise from local hospitals i.e., hospitals in the same city as the focal consumer i. Y^C_{st} captures the platform's time-varying marketing activities on the consumer side in province s. This variable is measured at the province level as this is the level that the platform plans marketing activities at.[13] W_{kt} captures the marketing activity of competing online platforms in city k at time t. We proxy for this via the use of the logarithm of the Baidu Index (a measure of search popularity similar to Google Trends) for the top nine competing physical health exam online platforms. X_{kt} are

[12]We assume that the relevant consumer network for a focal consumer i is comprised of other "near" consumers. N^C therefore includes the number of consumers who have adopted in the focal consumer's province.

[13]As mentioned earlier, the platform focuses most of its marketing effort (via its sales force) at hospitals, relying on word-of-mouth for the consumer side.

city-level time-varying characteristics, including the logarithm of GDP per capita, number of hospital beds per capita, and unemployment rate. η_k are city fixed effects to absorb the city-level time-invariant factors. ξ^C_{kt} are the remaining unobserved time-varying city-level factors and ϵ^C_{ikst} is consumer i's idiosyncratic preference towards the platform. Lastly, p^C_{ikst} represents the price for consumers to join the platform, which is zero in our context.

We assume U^C_{ikst} follows the Cobb-Douglas utility function and $G_C(\cdot)$ is linear in logs (see Berry et al. (1995), Chu and Manchanda (2016)). With $u^C_{ikst} \equiv log[U^C_{ikst}]$, we have

$$u^C_{ikst} = \beta_0 + \beta_1 ln(N^C_{s,t-\kappa}) + \beta_{2k,t-\tau} ln(N^H_{k,t-\tau}) + \beta_3 Y^C_{st} + \beta_4 W_{kt} + \beta_5 X_{kt} + \eta_k + \xi^C_{kt} + \epsilon^C_{ikst} \quad (2)$$

where $\beta_0 \equiv log[F_C(b^C)]$ represents consumers' intrinsic preference towards the online healthcare platform. β_1 measures the effect of the existence of other consumers on the platform from the same province on consumer i's platform adoption decision, i.e., the direct-network effect on the consumer side. $\beta_{2k,t-\tau}$ measures the heterogeneous effect of the existence of the hospitals on the platform on consumer i's platform adoption decision, i.e., the cross-network effect from the hospital side to the consumer side. We assume $\beta_{2k,t-\tau} = \beta_{20} + \beta_{21} H_{k,t-\tau}$, where $H_{k,t-\tau}$ represents the hospital size, measured by the average standardized number of health professionals among the joining hospitals on the platform in city k by time $t - \tau$.[14] The standardization for a given hospital is calculated as the number of health professionals in this hospital divided by that among all the hospitals in the same city. We do this in order to adjust for difference in scale and size of hospitals across markets. Since we do not directly observe the platform's marketing activities, we use a linear and quadratic province-specific time trend, plus the festival dummy to capture Y^C_{st}, with β_3 representing the effect size. β_4 denotes the effect of competitors' marketing activities on consumers' platform adoption. β_5 measures the effect of city socioeconomic characteristics and healthcare provision on consumers' platform adoption.

[14] In addition to the number of health professionals, we also collected information on the number of beds in each hospital and the number of outpatients treated by each hospital. These three metrics are highly correlated with each other. Of the three, we have the most complete data (fewest missing values) on the number of health professionals per hospital, so we use that as the measure of hospital size.

The utility from the outside option is normalized to be

$$u_{ikst}^{C,0} = \epsilon_{ikst}^{C,0} \tag{3}$$

Consumers' idiosyncratic preferences, ϵ_{ikst}^{C} and $\epsilon_{ikst}^{C,0}$, are assumed to follow an independent Type I extreme-value distribution. Then the probability of joining the platform is

$$Pr_{kst}^{C} = \frac{exp(\beta_0 + \beta_1 ln(N_{s,t-\kappa}^{C}) + \beta_{2k,t-\tau} ln(N_{k,t-\tau}^{H}) + \beta_3 Y_{st}^{C} + \beta_4 W_{kt} + \beta_5 X_{kt} + \eta_k + \xi_{kt}^{C})}{1 + exp(\beta_0 + \beta_1 ln(N_{s,t-\kappa}^{C}) + \beta_{2k,t-\tau} ln(N_{k,t-\tau}^{H}) + \beta_3 Y_{st}^{C} + \beta_4 W_{kt} + \beta_5 X_{kt} + \eta_k + \xi_{kt}^{C})} \tag{4}$$

while the probability of not joining the platform, $Pr_{kst}^{C,0}$, is equal to $(1 - Pr_{kst}^{C})$ or

$$Pr_{kst}^{C,0} = \frac{1}{1 + exp(\beta_0 + \beta_1 ln(N_{s,t-\kappa}^{C}) + \beta_{2k,t-\tau} ln(N_{k,t-\tau}^{H}) + \beta_3 Y_{st}^{C} + \beta_4 W_{kt} + \beta_5 X_{kt} + \eta_k + \xi_{kt}^{C})} \tag{5}$$

Let M_{kt}^{C} be the potential market size on the consumer side in city k at time t, which is proxied by Baidu Index of the broad keyword “health." We think this is a reasonable proxy as people who search “health" via the largest search engine in China are the people who would be potentially interested in buying physical health exams *online*. Then the platform's relative market share, i.e., the ratio between the platform's market share z_{kt}^{C} and the market share of the outside option $z^{C,0}$, is given by[15]

$$\begin{aligned} ln\frac{z_{kt}^{C}}{z^{C,0}} &= ln\frac{N_{kt}^{C}/M_{kt}^{C}}{(M_{kt}^{C} - N_{kt}^{C})/M_{kt}^{C}} \\ &= \beta_0 + \beta_1 ln(N_{s,t-\kappa}^{C}) + \beta_{2k,t-\tau} ln(N_{k,t-\tau}^{H}) + \beta_3 Y_{st}^{C} + \beta_4 W_{kt} + \beta_5 X_{kt} + \eta_k + \xi_{kt}^{C} \end{aligned} \tag{6}$$

The above equation serves as the basis for estimating the model of the consumer's adoption decision.

[15]Note that the estimated parameters adjust in scale to the chosen value of M_{kt}^{C} as the estimation is carried out in relative market shares. For more on why the exact value of the potential market size does not impact the results, see Chu and Manchanda (2016).

Hospital Adoption Decision

Turning to a hospital's decision to join the platform, we model the indirect utility of joining the platform for hospital j in city k province s at time t as

$$U_{jkst}^{H} = F_H(b^H)H_H(N_{k,t-\tau}^{H})G_H(N_{k,t-\kappa}^{C}, Y_{st}^{H}, Q_{jt}, W_{kt}, X_{kt}, \eta_k, \xi_{kt}^{H}, \epsilon_{jkst}^{H}) - p_{jkst}^{H} \quad (7)$$

where b^H is hospitals' average intrinsic preference towards the online healthcare platform. To capture the direct-network effect on the hospital side, $N_{k,t-\tau}^{H}$ measures the number of hospitals that have joined the platform at time $t-\tau$ in city k. To capture the cross-network effect from consumers to hospitals, $N_{k,t-\kappa}^{C}$ measures the number of consumers that have joined the platform at time $t-\kappa$ in city k. Y_{st}^{H} denotes the platform's time-varying marketing activities on the hospital side in province s. Q_{jt} summarizes the hospital characteristics, including the hospital type and the hospital size, measured by the number of health professionals. W_{kt} denotes the competing online platforms' marketing activities in city k at time t, measured by the logarithm of Baidu Index of the top nine competing platforms. X_{kt} are market-level time-varying factors, including the logarithm of GDP per capita, number of hospital beds per capita, and unemployment rate. η_k are city fixed effects to control for time-invariant city characteristics. ξ_{kt}^{H} are the remaining unobserved factors and ϵ_{jkst}^{H} are hospitals' idiosyncratic preferences towards the platform. Lastly, p_{jkst}^{H} represents hospitals' price of joining the platform in city k at time t, which is zero in our context (recall that hospitals only pay the negotiated discount only when a consumer buys a health test).

As with the consumer adoption utility, we assume that U_{jkst}^{H} follows the Cobb-Douglas utility function and $G_H(\cdot)$ is linear in logs. With $u_{jkst}^{H} \equiv log[U_{jkst}^{H}]$, we have

$$u_{jkst}^{H} = \alpha_0 + \alpha_1 ln(N_{s,t-\tau}^{H}) + \alpha_2 ln(N_{k,t-\kappa}^{C}) + \alpha_3 Y_{st}^{H} + \alpha_4 Q_{jt} + \alpha_5 W_{kt} + \alpha_6 X_{kt} + \zeta_k + \xi_{kt}^{H} + \epsilon_{jkst}^{H} \quad (8)$$

where $\alpha_0 \equiv log[F_H(b^H)]$ represents hospitals' intrinsic preference towards the online healthcare platform. α_1 measures the effect of the existence of other hospitals in the same city on hospital j's platform adoption, i.e., the direct-network effect on the hospital side. α_2 measures the effect of the number of consumers on hospitals' platform adoption decision, i.e., the cross-network effect from the consumer side to the hospital side. As before, Y_{st}^{H} is represented by a linear and quadratic time trend plus the festival dummy. Furthermore, in order to account for the additional marketing push by the platform to get hospitals to adopt in the second quarter of 2016, Y_{st}^{H} also includes dummy variables to represent this. The effects of Y_{st}^{H} are captured by α_3. α_4 measures the effect of hospital characteristics on the platform adoption decision. α_5 denotes the effect of competing online platforms' marketing activities on the hospitals' platform adoption. α_6 measures the effect of city socioeconomic characteristics and healthcare provision on hospitals' platform adoption.

The utility from the outside option is normalized to be

$$u_{jkst}^{H,0} = \epsilon_{jkst}^{H,0} \tag{9}$$

Hospitals' idiosyncratic preferences, ϵ_{jkst}^{H} and ϵ_{jkst}^{H}, are assumed to follow an independent Type I extreme-value distribution, so the probability of joining the platform is

$$Pr_{jkst}^{H} = \frac{exp(\alpha_0 + \alpha_1 ln(N_{s,t-\tau}^{H}) + \alpha_2 ln(N_{k,t-\kappa}^{C}) + \alpha_3 Y_{st}^{H} + \alpha_4 Q_{jt} + \alpha_5 W_{kt} + \alpha_6 X_{kt} + \zeta_k + \xi_{kt}^{H})}{1 + exp(\alpha_0 + \alpha_1 ln(N_{s,t-\tau}^{H}) + \alpha_2 ln(N_{k,t-\kappa}^{C}) + \alpha_3 Y_{st}^{H} + \alpha_4 Q_{jt} + \alpha_5 W_{kt} + \alpha_6 X_{kt} + \zeta_k + \xi_{kt}^{H})} \tag{10}$$

while the probability of not joining the platform, $Pr_{ikst}^{P,0}$, is equal to $(1 - Pr_{jkst}^{H})$ or

$$Pr_{ikst}^{P,0} = \frac{1}{1 + exp(\alpha_0 + \alpha_1 ln(N_{s,t-\tau}^{H}) + \alpha_2 ln(N_{k,t-\kappa}^{C}) + \alpha_3 Y_{st}^{H} + \alpha_4 Q_{jt} + \alpha_5 W_{kt} + \alpha_6 X_{kt} + \zeta_k + \xi_{kt}^{H})} \tag{11}$$

Unlike on the consumer side where we use the aggregated market share for estimation, we observe every single hospital's adoption decision after the sales team's visit. Thus, we will use maximum likelihood to estimate the above hospital adoption function.

Bargaining Model

We now illustrate how we bring the network effects and the bargaining process under a unified modeling framework. The basic intuition is as follows. Under Nash bargaining, if a hospital decides to join the platform, then it must be because the total payoff of the two parties from an entering into a contract is greater than the payoff from not entering. The contract terms - the discount and the clearing cycle - will then be determined by the generalized Nash bargaining solution.

For the sake of clarity, we present the model with the discount negotiation now (we discuss the clearing cycle negotiation in the next section). Hospital j's payoff via the platform, depending on the online sales R_{jt} and the discount d_{jt}, equals[16]

$$\Pi_{jt}^{H} = R_{jt}(1 - d_{jt}) \tag{12}$$

We assume hospital j's disagreement payoff, i.e., the payoff for the hospital when no contract is signed, $\Pi_{jt}^{H,0}$ to be zero in the negotiation as the hospital would gain nothing had the hospital not joined the platform. The platform's payoff with hospital j, Π_{jt}^{F}, is

$$\Pi_{jt}^{F} = R_{jt}d_{jt} + K_{jt} \tag{13}$$

The payoff consists of two parts. The first part $R_{jt}d_{jt}$ is the direct monetary payoff from selling physical health exams for hospital j. The second part K_{jt} illustrate the importance of network effects for the platform. In particular, K_{jt} represents the "value" of consumers attracted by hospital j's platform adoption. In other words, it is affected by the magnitude of the cross-network effects. Note that in a non-platform setting, K_{jt} would be 0 as there are no cross-network effects. The disagreement payoff $\Pi_{jt}^{F,0}$ for the platform is zero as the platform would gain nothing if hospital j had not adopted the platform.

The generalized Nash bargaining solution is given by maximizing the following generalized Nash product

$$(\Pi^{H} - \Pi^{H,0})^{\delta_{jt}}(\Pi^{F} - \Pi^{F,0})^{(1-\delta_{jt})} \tag{14}$$

where $0 \leq \delta_{jt} \leq 1$, and δ_{jt} and $(1 - \delta_{jt})$ represent the relative bargaining power of hospital j and the platform at time t, respectively.

[16]In our context, the list prices of the online health exams are set by the hospitals to be equal to the offline health exam prices. This is because the sales of online health exams account for a very small proportion of all sales for a given hospital. This provides little incentive for the hospital to set up a different process for setting online prices. As a result, we do not need to model the hospital's online list price setting process. Also, as the majority of the cost of physical health exams for hospitals is fixed (medical equipment cost and overheads) i.e., independent of online sales via the platform, we assume the variable cost to be zero.

After substituting the payoff functions into equation 14, we get the generalized Nash product as

$$(R_{jt}(1-d_{jt}))^{\delta_{jt}}(R_{jt}d_{jt}+K_{jt})^{(1-\delta_{jt})} \tag{15}$$

In order to maximize the generalized Nash product, the Nash bargaining solution needs to satisfy

$$\frac{\delta_{jt}}{1-\delta_{jt}}=\frac{1-d_{jt}}{d_{jt}+\frac{K_{jt}}{R_{jt}}} \tag{16}$$

subject to the constraint $0 \leq d_j \leq 1$. As noted above, the unique feature of this bargaining model for the (two-sided) platform compared with the traditional bargaining model is the presence of the term K_{jt}, which captures the value of the market expansion due to the cross-network effects. Without this term, the negotiated discount cannot equal 0 as hospitals' bargaining power should always be smaller than 1 in practice. With this term, however, it is possible that the negotiated discount equals 0 even when hospitals' bargaining power is smaller than 1. This is an important model features as over 20% of the agreed contracts had a zero discount (details in the next section).

After rearranging the function and allowing K_{jt} to be a function of the cross-network effect, CNE_{jt}, the Nash bargaining solution yields the following censored regression model

$$d_{jt}=\begin{cases} d^*_{jt}, & \text{if } d^*_{jt}\geq 0 \\ 0, & \text{otherwise} \end{cases} \tag{17}$$

$$d^*_{jt}=1-\delta_{jt}+\omega CNE_{jt}+\upsilon_{jt} \tag{18}$$

where CNE_{jt} is the cross-network effects of hospital j on the consumer side. Following the literature (e.g., Chu and Manchanda, 2016; Gandal et al., 2000), CNE is measured in elasticity terms, i.e., the effect on the market share on the consumer side when the number of hospitals increases by 1%, resulting in $CNE_{jt} \approx \tilde{\beta}_{2jt}(1-z^C_{kt})$, where $\tilde{\beta}_{2jt}$ is the estimated coefficient in the consumer adoption decision and z^C_{kt} is the platform's market share. ω is the impact of cross-network effects on the negotiated discount.

δ_{jt} is hospital j's relative bargaining power at time t, which is assumed to be heterogeneous across four hospital types and influenced by z^C_{kt} (the platform's consumer market share in city k). In other words, the relative bargaining power of the platform varies across hospitals and changes over time as the consumer market share grows. Specifically, we have $\delta_{jt} = \theta z^C_{kt} + \delta_{pubA} I(hospital_j = public\ A\ hospital) + \delta_{pubB} I(hospital_j = public\ B/C\ hospital) + \delta_{pri} I(hospital_j = private\ hospital) + \delta_{sc} I(hospital_j = special\ clinic)$, where the subscript k is omitted in δ_{jt} for simplicity.

We highlight the specific model parameters that allow us to test our hypotheses below in Table 2.

Table 2. Model Parameters and Hypotheses

Parameter	Definition	Hypothesis	Equation
β_1	Direct network effect on the consumer side	H1a	(2)
α_1	Direct network effect on the hospital side	H1b	(8)
β_2	Cross network effect from hospitals to consumers	H2a	(2)
α_2	Cross network effect from consumers to hospitals	H2b	(8)
β_{21}	Moderating effect of hospital size on CNE	H3	(2)
ω	Impact of CNE on bargaining outcome	H4	(17)
θ	Impact of the platform's market share on its relative bargaining power	H5 & H7	(17)
δ_{pubA}, δ_{pubB}, δ_{pri}, and δ_{sc}	Relative bargaining power of the four types of hospitals towards the platform	H6 & H7	(17)

Data

Our data span over four and half years starting from the platform's launch date on August 1, 2015 to December 31, 2019. The platform has been growing rapidly on both the consumer and hospital sides. By the end of 2019, around 3 million consumers and 1,160 hospitals have joined the platform. Figure 3 shows the growth patten on the consumer side and on the hospital side. The consumer side follows a clear exponential growth pattern while the hospital side growth is relatively linear. The dip on the consumer side around each February is caused by the Chinese New Year. The spike on the hospital side around the second quarter in 2016 was caused by a huge push by the sales team's effort (as mentioned earlier, we have explicit controls for these events in our model). Figure 4 plots the geographic distribution of the two sides of the platform. The adoption of the platform is more concentrated in the more developed east and south regions of China. Since consumers need to visit hospitals to receive the service, we see a high geographic correlation between the two sides. Again, as mentioned earlier, this is the reason why we construct our variables at the local market and/or network level.

Figure 3. Platform Growth

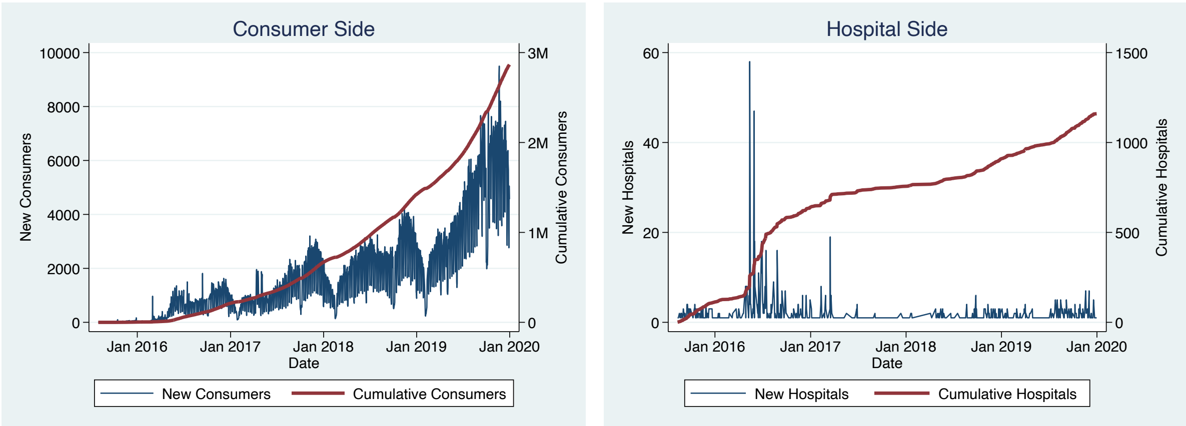
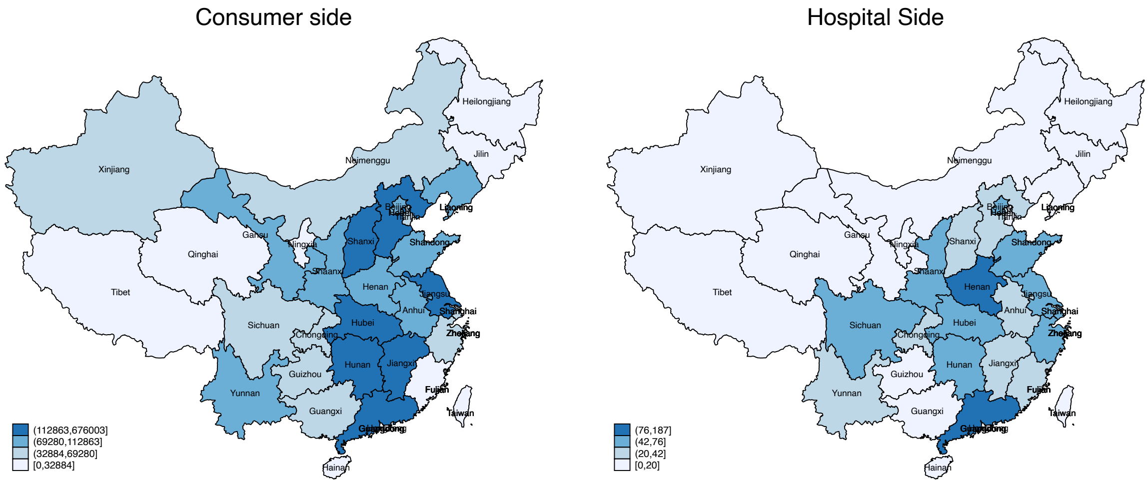


Figure 4. Geographic Distribution



The platform employs sales teams to convince hospitals to join the platform. After a sales lead is generated, a sales person calls the hospital to schedule a visit. If a prospect is identified, the sales person visits the hospital to meet the relevant decision makers via meetings, lunches etc. Over the sample period, the company made 11,433 hospital visits to 2,497 unique hospitals, and converted 1,160 hospitals across 202 cities. On average, it took the sales team about 2.4 visits to convert a hospital with another 4.4 visits to maintain the relationship.[17]

To understand the expansion strategy of the platform, Table 3 presents the summary statistics of the market characteristics over time. The markets are defined at the city level due to the nature of the service. The platform started in big cities (with higher levels of GDP, population, unemployment, and total number of hospital beds) and then expanded into smaller cities over

[17]Of the 1,160 joining hospitals, 40 hospitals (3.4%) left the platform by the end of the sample period. Note that the stay or leave decision is implicitly captured our hospital adoption model.

time. Table 4 summarizes the number of consumers and the number of hospitals that joined the platform across markets over time. The last column in this table shows that the size of the joining hospitals, measured by the average number of health professionals, has been increasing from 2015 to 2019. This implies that the proportion of bigger hospitals that joined the platform is increasing over time.

Table 3. Summary of City Characteristics

		GDP (billion Yuan)		Population (thousands)		Unemployment (thousands)		Number of Hospital Beds	
Year	# Cities	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2015	46	618.3	517.6	676.2	504.0	56.1	54.7	40,587	30,453
2016	143	402.0	461.1	552.5	380.3	39.0	49.0	30,359	24,254
2017	156	285.6	484.1	550.3	369.2	36.3	42.7	26,964	22,771
2018	169	428.1	514.1	544.1	366.4	34.0	35.9	27,620	23,522
2019	202	416.6	531.6	524.7	352.5	31.3	34.3	27,020	22,934

Note: We report the number of cities where at least one hospital has joined the platform. GDP, population, unemployment, and the number of hospital beds are measured among these cities.

Table 4. Summary of Consumers and Hospitals

		Number of Registered Consumers		Number of Joined Hospitals		Avg. Number of Health Professionals	
Year	# Cities	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2015	46	50.4	125.1	2.4	2.2	746.5	698.1
2016	143	1,301.6	2,602.2	3.9	5.8	852.3	641.7
2017	156	3,785.2	7,344.2	4.4	7.2	932.9	651.9
2018	169	7,594.9	16,704.6	5.0	8.6	967.5	682.2
2019	202	12,950.3	28,588.7	5.5	9.3	1,076.0	592.0

Note: We report the number of cities where at least one hospital has joined the platform. Number of registered consumers, number of joined hospitals and the average number of health professionals per hospital are measured among these cities.

There are different types of hospitals that offer physical health exams in China. These comprise public hospitals, private hospitals, and special clinics. Public hospitals are further classified by the government into three tiers - A, B, and C - based on the size and the quantity/quality of medical care, teaching and research, with A being the highest on these attributes. Since the number of public C hospitals on the platform is less than 10, we group public B and

C hospitals together in the analysis. Table 5 breaks down the number of hospitals that joined the platform across different types, the number of health professionals, and the negotiated contract outcomes. As can be seen from the table, about 50% of them are public A hospitals, 17% are public B/C hospitals, 14% are private hospitals, and the remaining 18% are special clinics. The size of the hospitals, measured by the number of health professionals, is ranked as public A, public B/C, private, and special clinics, from largest to smallest. The negotiated discount, interestingly, follows the opposite order to the size of the hospitals. It is worth mentioning that about 60% of the negotiated discounts equaled zero in 2016 and this number decreased to 23% in 2019. In other words, the platform earned zero profits from many hospitals initially. Such a penetration pricing strategy is prevalent in platform markets as they are typically willing to sacrifice short-term profit for long-term growth during the introduction and expansion phase. The average clearing cycle ranges between 10 days and 15 days. As explained earlier, hospitals tend not to treat the clearing cycle as an important contract term, leading to no systematic patterns between it and the hospital type.

Table 5. Summary of Hospital Contracts

		Number of Health Professionals		Discount Level		Clearing Cycle (day)	
Hospital Type	# of Hospitals	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Public A Hospital	582	1,825.2	1,193.5	0.062	0.083	11.1	15.8
Public B/C Hospital	202	610.9	463.2	0.081	0.121	9.8	13.5
Private Hospital	163	375.1	341.1	0.108	0.130	9.9	13.4
Special Clinic	213	181.2	76.3	0.199	0.187	14.5	14.4
Total	1,160	1,108	1,141.2	0.096	0.131	11.4	15.0

Note: The reported discount level and clearing cycle are averaged among all the contracts signed given a hospital type.

Estimation and Results

Adoption Decision

We now present the results from our empirical analysis that help us to test our hypotheses. Before we get to the results, we need to explain the identification of our parameters and address potential endogeneity concerns.

For the consumer adoption decision, as we discussed earlier, our data can be seen as a panel with cities providing the cross-section and months providing the time-series. Thus, the number of consumers who adopt varies across both cities and months, helping us to identify the parameters in the consumer adoption model. For the hospital adoption decision, our data include adoption outcomes after each sales team's visit. The adoption decision varies across hospitals, across cities and across months, providing us the variation for identification of the hospital adoption model.

A potential challenge to the above identification strategies is that of endogeneity. There are two potential sources of endogeneity in our context. These are omitted variables and simultaneity. For example, it is possible that the linear and the quadratic time trends plus other time dummies do not capture the platform's sales and marketing activity completely. To address this issue, we use the control function approach with instrumental variables (IVs) (Petrin and Train, 2010; Wooldridge, 2015). We use two sets of IVs.

The first instrument that we use is for the number of joining hospitals. We use the number of approached hospitals i.e., all the hospitals that were approached by the platform's sales team in that time period, as the instrument. This instrument satisfies both the relevance condition, i.e., it is correlated with the endogeneous variable, and the exogeneity condition, i.e., it does not directly affect the outcome variable. It satisfies the relevance condition because the number of approached hospitals affects the number of joining hospitals. It satisfies the exogeneity condition because it does not directly affect consumers' joining decision as consumers are not aware of how many hospitals have been approached by the sales teams. The weak identification test (Cragg-Donald Wald F statistic) equals 679.5, higher than the critical value of 10 (Stock and Yogo, 2005), for this instrument.

The second instrument we use is for the number of joining consumers. We use the air quality at the city level as the instrument. Specifically, we use multiple measure of air quality that are publicly available - overall air quality (AQI), levels of particulate matter ($PM2.5$, $PM10$), and levels of other air gases (CO, NO_2, O_3, and SO_2). This set of instruments is relevant as air quality affects consumers' health awareness and concern, changing their interest in health tests. It satisfies the exogeneity condition as there is no reason for it to affect the hospitals' online platform adoption decision. The weak identification test (Cragg-Donald Wald F statistic) equals 242.7, higher than the critical value of 10 (Stock and Yogo, 2005), for this set of instruments.

In order to address the simultaneity concern, we use the one-month lagged measures of the number of joining consumers and the number of joining hospitals instead of the contemporaneous measures.

The results for the consumer adoption model are given in Table 6. The first two columns report the base coefficient estimates while the final two columns report the coefficients with the consideration of the heterogeneous cross-network effects from the hospital side to the consumer side. Columns (1) & (3) report the ordinary least squares (OLS) results and columns (2) & (4) report the estimates with the IVs. As can be seen from the table, the use of IVs changes the results somewhat, with the most salient difference in the cross-network effect (which are bigger with IVs). We focus on the IV approach results in the discussion below.

The coefficients related to our hypotheses pertaining to the network effects are shown in the top part of the table. The coefficient of the number of consumers, representing the direct-network effect, is positive and statistically significant ($p < .01$), supporting H1a. In terms of the magnitude, a 1% increase in the consumer base in the province leads to about 0.81% increase in the consumer base in a city in the following month. As noted earlier, this suggests that mechanisms such as positive word-of-mouth, quality signaling, and observational learning play an important positive role in terms of the platform's growth on the consumer side.

The positive cross-network effect from hospitals to consumers is statistically significant ($p < .01$), supporting H2a both with and without hospital heterogeneity. Without considering hospital heterogeneity, the cross-network effect is 0.36 on average (column (2)), i.e., 1% increase in the number of hospitals leads to 0.36% increase in the consumer base in the same city. In an average city, this means that one more hospital's adoption of the platform will attract 277 consumers (s.d. = 50.3) to the platform in the following month.

Column (4) focuses on the heterogeneous cross-network effects. With an increase in the the hospital size, i.e., the number of health professionals, the number of consumers that this hospital will be able to attract also increases. This positive moderating effect of hospital size

Table 6. Consumer Adoption Decision

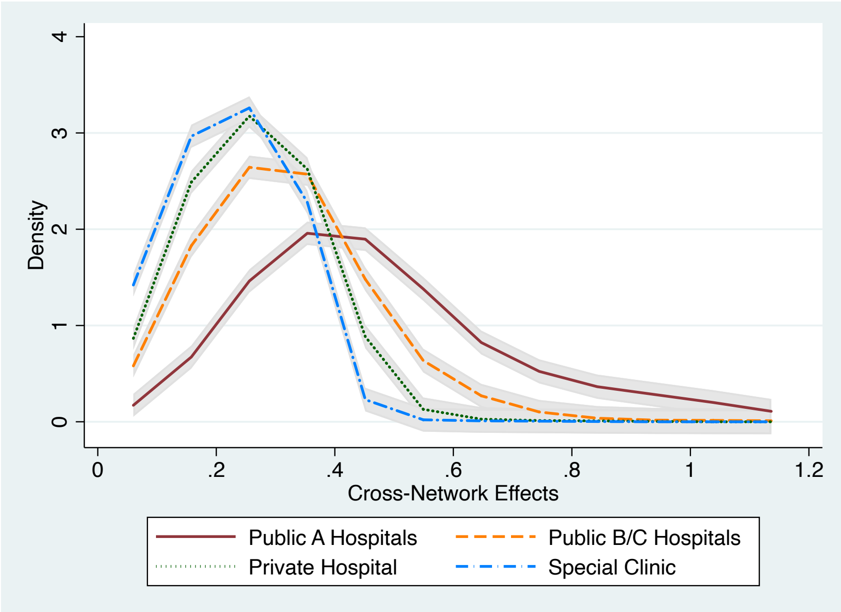
	Consumer Relative Market Share			
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Network Effects				
ln(No.Consumers)	0.84***	0.83***	0.84***	0.81***
	(0.013)	(0.014)	(0.013)	(0.016)
ln(No.Hospitals)	0.17***	0.36***	0.13***	0.20***
	(0.027)	(0.067)	(0.030)	(0.061)
ln(No.Hospitals)*Avg. Size			0.0041***	0.016***
			(0.0013)	(0.0045)
Market Characteristics				
ln(Competition Index)	-0.0067**	-0.0061**	-0.0070**	-0.0069**
	(0.0027)	(0.0027)	(0.0027)	(0.0028)
ln(GDP Per Capita)	-0.16***	-0.17***	-0.16***	-0.15***
	(0.028)	(0.028)	(0.028)	(0.029)
Hospital Beds (per 1,000 people)	0.031***	0.031***	0.031***	0.029***
	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Unemployment Rate	0.0093	0.018	0.0077	0.013
	(0.022)	(0.022)	(0.022)	(0.022)
Festival Dummy	-0.0075	-0.013	-0.0047	-0.0093
	(0.021)	(0.021)	(0.021)	(0.021)
Time Trends	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Control Function		Yes		Yes
No. of Observations	12,935	12,935	12,935	12,935

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

on the cross-network effect is statistically significant ($p < .01$), supporting H3. In order to clearly illustrate the difference in the cross-network effects across hospital types, Figure 5 plots the entire distribution of the estimated cross-network effect for each type. Each line represents distribution of the cross-network effect for a hospital type[18], and the grey area represents the 95% confidence interval around this effect based on the model estimates. The figure indicates that public A hospitals on average have the highest cross-network effects (mean = 0.51, s.d. = 0.31), followed by public B/C hospitals (mean = 0.32, s.d. = 0.14), private hospitals (mean = 0.26, s.d. = 0.06), and then special clinics (mean = 0.23, s.d. = 0.03). The figure suggests that substantial heterogeneity exists both across (different types of) and within (a given type

[18]These lines are generated as Epanechnikov kernel density functions (Epanechnikov, 1969).

Figure 5. Cross-Network Effects Across Hospital Types



of) hospitals. Furthermore, while the distributions are distinct, there is some overlap across hospital types in terms of the cross-network effects.

In addition to the direct-network effects and the cross-network effects, the market characteristics present further interesting insights on the consumer adoption decision. First, we see that the competing platforms' marketing activities negatively impact the consumer adoption likelihood on the focal platform. Second, surprisingly, we find that the higher the GDP per capita, the lower the relative market share on the consumer side in a city. This may be driven by a unique feature of employee benefits in China. Many large companies offer complimentary physical health exams to their employees, making individual level health exam purchases unnecessary. As large companies are more prevalent in large cities with higher GDP per capita, the platform ends up having relatively lower market share. Third, we find that the healthcare availability and access in a city, measured by the number of hospital beds per capita, is positively correlated with the platform's consumer market share. One of the underlying reasons can be that the healthcare access is positively correlated with awareness about health issues leading to higher market penetration for the platform's services. Lastly, we do not see any strong correlation between the unemployment rate and the market share of the platform, nor a strong impact from the festival dummy.

We next turn to the results from the hospital adoption model. Table 7 reports coefficient es-

Table 7. Hospital Adoption Decision

	Hospital Adoption Decision		Hospital Adoption Odds-Ratio
	Logit	IV	IV
Network Effects			
Ln(No. Hospitals)	2.35***	2.42***	11.30***
	(0.10)	(0.11)	(1.08)
Ln(No. Consumers)	0.23***	0.89***	2.43***
	(0.050)	(0.13)	(0.35)
Hospital Characteristics			
Public A Hospital	-1.26***	-1.28***	0.28***
	(0.088)	(0.088)	(0.024)
Public B/C Hospital	-1.08***	-1.11***	0.33***
	(0.088)	(0.089)	(0.029)
Private Hospital	-0.33***	-0.38***	0.68***
	(0.094)	(0.095)	(0.063)
No. Health Prof. (k.)	0.10***	0.12***	1.13***
	(0.027)	(0.027)	(0.29)
Market Characteristics			
ln(Competition Index)	-0.059***	-0.048***	0.95***
	(0.011)	(0.011)	(0.011)
ln(GDP Per Capita)	0.30	0.54**	1.72**
	(0.26)	(0.26)	(0.46)
Hospital Beds (per 1,000 people)	-0.38***	-0.55***	0.58***
	(0.083)	(0.090)	(0.054)
Unemployment Rate (%)	0.78***	0.51***	1.66***
	(0.11)	(0.12)	(0.21)
Festival Dummy	0.32***	0.39***	1.48***
	(0.12)	(0.12)	(0.20)
Special Month	-0.37***	-0.76***	0.47***
	(0.071)	(0.11)	(0.050)
Time Trends	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Control Function		Yes	Yes
No. of Observations	11,176	11,176	11,176

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels. “Special Clinics" is the reference hospital type.

timates for the network effects, the effects of hospital characteristics, and the effects of market characteristics in hospitals’ joining decision. Column (1) reports the baseline logistic regression results. Column (2) reports the control function results with the instruments. In order to facilitate interpretation, we transform the results in column (2) to an odds-ratio (the probability that the event will occur divided by the probability that the event will not occur) and report that in column (3). From the table, we can see that the direct-network effect is positive and statistically significant ($p < .01$), supporting H1b. In terms of magnitude, holding all other independent variables constant, we see that a 1% increase in the number of participating hospitals leads to 10.3% increase in the odds of a hospital's adoption [$(11.30 - 1) \times 1\% = 10.3\%$]. The cross-network effect (from consumers to hospitals) is also positive and significant ($p < .01$), supporting H2b. Again, in terms of magnitude, a 1% increase in the consumer base leads to 1.43% increase in the odds of a hospital's adoption [$(2.43 - 1) \times 1\% = 1.43\%$].

Regarding the hospital types, we find that the probability of adopting the platform from highest to lowest is special clinics (the default category), private hospitals, public B/C hospitals, and public A hospitals (all else held equal). This ranking is somewhat expected as Public A hospitals are heavily used as they have (or are perceived to have) the best doctors, medical equipments, and medical research among all types. As a result, the online revenue from joining the platform may not be as attractive to public A hospitals as to special clinics. Public B/C hospitals are also seen as being better than private hospitals. Given a hospital type, we see that hospital size, measured by the number of health professionals, is positively correlated with a hospital's probability to adopt the platform.

Lastly, similar to the consumer side, we find that the competing physical health exam online platforms' marketing activities have a negative impact on hospitals' adoption decision. GDP per capita is positively correlated with a hospital's adoption likelihood. Furthermore, the lower the healthcare provision in a city or the higher the unemployment rate, the higher the likelihood of hospitals to adopt the online platform.

Contract Bargaining

We next turn to the bargaining model. The identification of the parameters in this model comes from the variation in bargaining outcomes across 5,839 (original and re-negotiated) contracts between hospitals and the platform in our data. We estimate this model using maximum likelihood approach. Note that cross-network effects enter as a covariate (equation 17) and as they are estimated parameters rather than data, we adjust the standard errors in the contract bargaining model using the Murphy-Topel approach (Hardin, 2002; Hole, 2006; Murphy and Topel, 2002).

Table 8. Contract Bargaining

	Discount		Discount&Clearing Cycle	
	Mean	Std. Err.	Mean	Std. Err.
ω	-0.114***	(0.0129)	-0.112***	(0.0118)
θ	-0.128**	(0.0570)	-0.176***	(0.0523)
δ_{pubA}	0.901***	(0.0076)	0.886***	(0.0071)
δ_{pubB}	0.898***	(0.0066)	0.879***	(0.0062)
δ_{pri}	0.859***	(0.0077)	0.848***	(0.0072)
δ_{sc}	0.752***	(0.0058)	0.738***	(0.0054)
No. of Obs.	5,839		5,839	
No. of Obs. Left-censored	1,768		1,341	

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Table 8 reports the coefficient estimates. We first focus on the left panel, which presents the result for the negotiated discount. We find that ω – the impact of cross-network effect on the discount level – is negative and statistically significant ($p < .01$). This provides support for H4, which pertains to the effect of the cross-network effects on bargaining outcomes. Recall, that this is the critical (and novel) hypothesis that provides the theoretical link between the network effects literature and the bargaining literature. In terms of the magnitude, a one unit increase in the cross-network effect leads to a 0.114 decrease in the negotiated discount.

In terms of financial impact, we use the results described in the previous section that the average cross-network effects are highest for public A hospitals at 0.51 and lowest for special clinics at 0.23. This difference in cross-network effects between the two types implies a 0.032 $(= (0.51 - 0.23) * 0.114)$ difference in the negotiated discount. This is a substantial number as this implies that the profit would change from $x\%$ to $(x + 3.2)\%$ for the platform. Given that 582 public A hospitals have joined the platform with an average annual sales of 576.7k Yuan per hospital via the platform, had these public A hospitals' negotiated discounts been the same as that of special clinics, the platform would gain an additional profit (as this is purely incremental revenue with no additional cost) of 10.7m Yuan [$(576.7k * 582 * 0.032 \approx 10.7m)$], which is about 8.7% of the platform's revenue in 2019 [$10.7m/123m$].

Next, we turn to bargaining power. As noted in our theoretical motivation, the relative bargaining power for the platform and a hospital is determined by the platform's consumer market share and the type of the hospital.

The coefficient θ captures the impact of the platform's consumer market share on the relative bargaining power of a hospital. In support of H5, the significant and negative coefficient ($p < 0.05$) suggests that a hospital's relative bargaining power decreases as the platform's consumer market share grows. In other words, the platform's bargaining increases as its consumer market share grows. In terms of magnitude, a 10% increase in the consumer market share of the platform leads to a hospital's bargaining power decreasing by 1.28% (on average). Given that the platform's average consumer market share across all cities was 7% in 2019, this suggests that the relative bargaining power of the four different types of hospitals (public A, public B, private, special clinic) and the platform equals $(0.892, 0.108)$, $(0.889, 0.111)$, $(0.850, 0.150)$, and $(0.743, 0.257)$ respectively.

In terms of how the hospital types affect bargaining power, a comparison of the δ coefficient across hospital types shows that public A hospitals have the largest bargaining power, followed by public B hospitals, private hospitals, and special clinics. The estimated bargaining power is not statistically significantly different between public A and public B/C hospitals. However, the bargaining power of public hospitals is much stronger than private hospitals and special clinics ($p < 0.01$), which supports H6. To put it into context, all else being equal, for a $\$100$ surplus between a hospital and the platform, a public A hospital would be able to receive $\$15$ more from the platform compared to a special clinic.

One unique aspect of our data is that it includes not only the negotiated discount but also a “non-monetary" negotiated contract term of clearing cycle. Clearing cycle is critical for the platform as it generates interests and alleviates liquidity constraints. To study this two-attribute bargaining, we incorporate the negotiated clearing cycle into the bargaining framework by converting the clearing cycle into “discount" terms. Specifically, we assume the platform is able to generate interest on received revenue at the credit card annual percentage rate (APR), which is 0.05% per day.[19] Thus, a 28-day clearing cycle is equivalent to a 1.4% (28 $\times$ 0.05%)

[19]The interest rate is set by The People's Bank of China. http://www.pbc.gov.cn/zhengwugongkai/4081330/4081344/4081395/4081686/4085953/index.html Our conversation with the platform's CFO revealed that it is quite

discount.

The right panel of Table 8 presents the result for the negotiated discount plus the converted clearing cycle. The results, shown in the right panel, are broadly similar with the single-attribute bargaining results for the negotiated discount. After the clearing cycle is accounted for, two patterns arise. First, the platform's consumer market share gives the platform an even stronger bargaining power as the magnitude of θ is bigger on the right panel. Second, the estimated baseline bargaining power (comparing $\delta's$ on the right panel to the left) is lower for all the four types of hospitals (in a range of 0.01 to 0.02), again implying the bargaining power is higher for the platform. While this difference seems arithmetically "small," it is important to note that it is statistically significant ($p < .01$), providing support for H7. Also, this small increase in the bargaining power has a big impact on the platform's working capital requirement and profits, especially in its early days. For example, the estimated 0.01 - 0.02 increase in the platform's bargaining power translates into an extra 1.23 to 2.46mm Yuan in 2019 given that the platform's 2019 revenues were 123m Yuan.

Managerial and Consumer Implications

Profitability and growth are both critical to an online platform's success. The former as it allows the business to run and the latter as it helps the flywheel start moving faster. As these two objectives often move in opposite directions, online platforms need to find a way to find a balance between them, especially in the early years of the business. For the online healthcare platform in our context, the trade-off between these objectives can be seen based on our results. For example, public A hospitals have the highest cross-network effects, but the platform has lowest relative bargaining power vis-a-vis public A hospitals. This implies that the platform's contracting with a public A hospital would bring in highest growth potential but may result in lowest profit compared to contracting with other types of hospitals.

We carry out a series of simulations to show how the platform can balance the two conflicting objectives of profitability and growth. Specifically, we consider four (simulated) scenarios.

difficult for the smaller private start-up firms like the platform to get loans from traditional banks. Thus, they need to borrow from shadow banks whose interest rates are usually much higher than the credit card APR. Thus, using credit card APR provides us a conservative estimate on the value of the clearing cycle.

Instead of starting with zero hospitals on the platform, we assume the platform started with one hospital of each type in each city at time zero. In other words, the platform started with one public A or one public B/C or one private or one special clinic at time zero, representing four different scenarios. We then contrast the impact of this four types of “initial seeding" on the platform growth via the growth curves over time relative to the actual observed growth.

Figure 6. Ratios of Simulated/Observed Number of Consumers and Hospitals by Seeding Hospitals

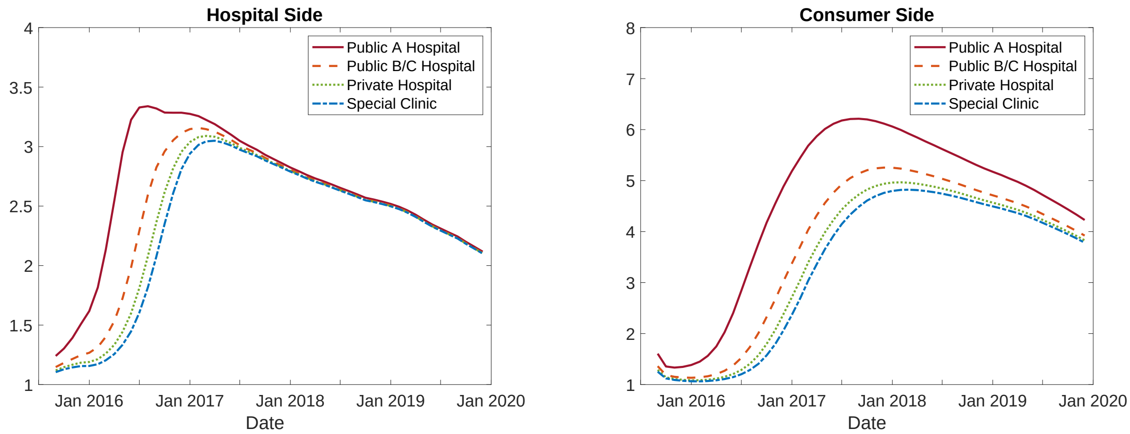
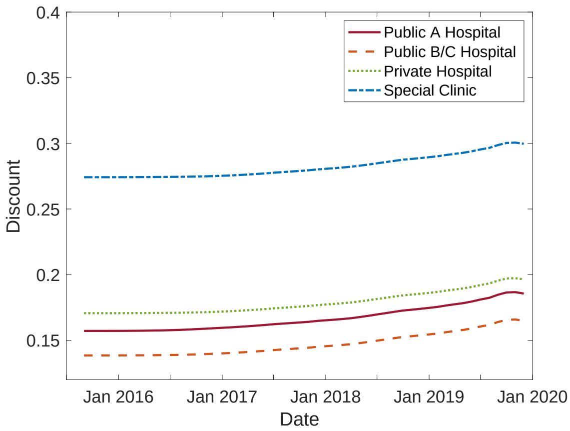


Figure 6 plots the ratios of simulated number of hospitals and number of consumers over the observed (actual) numbers. There are two key insights that can be drawn from this figure. First, we find that relative to the observed growth, seeding hospitals at the beginning leads to a significant increase in both number of consumers and number of hospitals. The ratio between the simulated numbers and the observed numbers increases in the early months, peaks around the end of the first year, and then gradually decreases. This is the result of the flywheel effect created by the positive hospital-to-consumer cross-network effects and the positive consumer-to-hospital cross-network effects, as also the positive direct-network effects on both sides. The positive impact of initial seeding is not only significant but also long-lasting, i.e., the ratio continues to be greater than one at the end of 2019, four and half years after the platform was established. Second, we find that the initial seeding with public A hospitals leads to the largest increase in the growth of the platform. This is expected as public A hospitals have the highest cross-network effects. The heterogeneity in the hospital-to-consumer cross-network effects across four types of hospitals manifests itself over time. The gap across the four types increases until about the end of the first year and diminishes afterwards.

Figure 7. Simulated Discounts Among Seeding Hospitals



Next we explore the impact of initial seeding of four types of hospitals on the platform's profitability. With the simulated number of consumers and number of hospitals, we calculate the discount amounts that would be agreed upon by the two parties in each of the simulated scenarios. Figure 7 plots the results. Again, two key insights can be drawn from this figure. First, the discounts grow over time as the platform grows. This is intuitive as the larger the consumer market share the platform commands, the higher the platform's bargaining power, and thus the higher the agreed upon discount. Second, we find that the discount for the platform is highest with special clinics, followed by private hospitals, public A hospitals, and lastly by public B/C hospitals.

The above simulations show the benefit from the initial seeding of hospitals to the platform. We next turn to the potential costs involved in each of the simulated scenarios. The costs of having a hospital join the platform depend on two things. The first is the hospital's adoption probability after the sales team's visit and the second is the cost of sales teams' visit. We use the observed adoption probability from the first three months to approximate across the different types of hospitals to obtain the first set of numbers. These are 20.5%, 20.6%, 27.3% and 46.3%, for public A, public B/C, private and special clinics respectively. Regarding the visit cost, the platform's CEO revealed that as the difficulty in signing a contract increases with the bureaucracy of a hospital, the costs are roughly proportional to the hospital size. Due to confidentiality concerns, we use X to represent the cost per visit to a special clinic, then the visit cost will be about $10X$, $3.4X$, $2.1X$ for public A, public B/C and private hospitals, respectively. With the above information, we conduct a back-of-envelope calculation to obtain the total cost associated with each scenario. We find that the costs associated with seeding special clinics is about $437X$ and the ratios for the other three scenarios will be 22.7, 7.6, and 3.5 over the special clinics.

Armed with these benefits and costs, the platform can make more informed decisions about the balance between profitability and growth and the subsequent resource allocation. For example, if the platform is under pressure to show (short-term) profits or is facing liquidity constraints, then it should allocate its resources towards converting special clinics. This is because it would lower its upfront costs, yielding quicker revenues and profits. Of course, this would also slow down growth. On the other hand, if the focus of the platform is on the fastest possible growth, then it should allocate its resources towards converting public A hospitals. This is because they engender the highest growth pattern for the platform. The downside is that converting these hospitals is a high-cost exercise. Interesting, our simulations show that the platform may want to spend less effort on public B/C hospitals initially. Compared to converting public A hospitals, converting public B hospitals brings in neither higher profits nor higher growth. This is caused by the fact that the increase in the platform's relative bargaining power induced by the increased market share of seeding public A hospitals is large enough to compensate for the platform's lower bargaining power towards public A hospitals. Finally, the platform can also investigate more complex resource allocation strategies, where the focus is not on just a single hospital type, but on the optimal portfolio of hospital types at different stages in the evolution of the platform.

The above discussion focuses on the implications of our research for the platform. However, consumers also benefit from joining the platform. As noted earlier, the benefit to consumers come from savings in time, hassle costs and medical (consultation) costs. In order to quantify the benefit to consumers, we carry out a back-of-the-envelope calculation to provide a sense of the magnitude of the benefit. First, we look at the benefit from shortened waiting times. The average waiting time in Chinese hospitals is about half an hour (Sun et al., 2017) and the average minimum hourly wage in China is 18 Yuan (Statista). This implies that for a typical transaction, the consumer gets a benefit equivalent to 9 Yuan (18 Yuan/hour * 0.5 hours). Second, we look at the benefit from the free doctor consultation provided on the platform. The average price of a ten minute remote (phone or online) consultation with an attending physician in China is 23 Yuan (Li et al., 2019), which implies a 23 Yuan gain on the physical health exam platform. Thus, the total benefit from these two sources is equivalent to 32 yuan (9 Yuan + 23 Yuan).

Therefore for an individual consumer, the use of the platform provides a saving equal to 1.78 hours of wages (32/18). At the aggregate level, with each of the four types of initial seeding of hospitals, the consumer base would have increased to about four times of the observed number by the end of 2019 (based on the analysis above). With the observed consumer base being 2.6 million by the end of 2019, this suggests a net incremental addition of 2.6 X 3 = 7.8 million consumers. Given the saving of 32 Yuan per consumer, the aggregate gain is 268.8 million Yuan, about twice the platform's revenue in 2019. Note that these estimates (at the individual and aggregate levels) are conservative as we do not include the benefit coming from the savings on travel (to the hospital) cost as well as the access to the free access to the discussion board on the platform.

Conclusion

This paper adds to the small but growing body of literature that looks at new online business models that have the potential to increase access and availability to healthcare for large populations. The business model that the paper focuses on is online platforms. The key to growth of such platforms is obtaining adoption on both sides - consumers and health care providers - in a manner that the installed base on each side increases the installed on the other side. At the same time, the platform needs to also consider the financial metrics - revenues, costs and liquidity - that keep it going as a viable business. Given that healthcare providers are typically institutions, platforms need to engage in negotiation to arrive at mutually agreed upon contracted terms of business in order to get them to join.

This setting necessitates a richer theoretical perspective than is typically found in the literature. Specifically, while the network literature speaks to platform growth and the bargaining literature to business contract negotiation, they operate in isolation. Therefore, in this paper, we draw upon both sets of theoretical literature to combine them in a bigger theoretical framework. The key link between the two literatures is the interplay between cross-network effects and bargaining outcomes. The intuition is that agents that have a higher cross-network effect i.e., can induce a larger number of agents on the other side of the platform to join, have higher bargaining power. This in turn leads them to get better contract terms from the platform. These contracts, once signed, affect the growth of the platform as well as its profitability which in turn affects the joining probability of other agents. We formalize the insights from our theoretical framework into testable hypotheses.

We specify an empirical model whose parameters allow us to test our hypotheses. The model spans the consumer adoption decision, the hospital adoption decision and the bargaining process between the platform and the hospital. We estimate our model on novel data from a large and fast-growing online healthcare platform in China (the world's second largest MedTech market). Our data are available from the inception of the platform. The contracts signed between the hospital and the platform are multi-attribute in nature (spanning pricing and payment terms). Our findings show strong evidence of positive network effects, both direct and cross. We find that the cross-network effects vary considerably across different hospital types, something that previous literature has not investigated. However, our most novel and key finding, as hypothesized, is that agents with stronger cross-network effects obtain better contract terms, all else being equal. We also show that when agents are endowed with stronger attributes e.g., consumer market share for the platform or brand/prestige for the hospital, they are able to obtain proportionally more of the total value created in the bargaining process.

In addition to the theoretical validation, we translate our results into direct implications for the platform via a series of simulations. Specifically, we look at the tension between profitability and growth objectives for the platform. The results from the simulations allow the platform to choose which types of hospitals to target at different points in its evolution based on the weights attached to these two objectives. Finally, we carry out a simple analysis that suggests that the typical consumer who signs up for the platform gets an additional (conservative) benefit equal to two hours of average wages.

The paper does suffer from some limitations. First, the data come from one online healthcare platform in one market. Having said that, we note that our theoretical framework is quite general and can be applied to online platforms operating in any setting where at least one party goes through a negotiation process. Second, the online physical health exams provided by the platform are relatively simple healthcare procedures that are more preventative in nature. Third, while we use proxies to capture the impact of competitive presence on the focal platform's growth and profitability, we do not have detailed data on their actions. Finally, without access to data on offline physical health exams, it is hard for us to quantify precisely the extent to which online platforms expand the market for physical health exams overall. We hope that future research can address these limitations.

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